**The International Conference on Management, Business, Economics, Law and Technology (COMBELT-2025)**

*August 01st, 2025, Danang, Vietnam*

# Adoption of Artificial Intelligence in Vietnamese SMEs Using An Integrated TAM-TOE Model

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**ABSTRACT**

This study investigates the factors influencing the adoption of Artificial Intelligence (AI) in small and medium-sized Enterprises (SMEs) in Vietnam using an integrated TAM-TOE model. Targeting employees, managers, and CEOs, it employs a quantitative approach with a sample of 309 participants from SMEs. Data was analyzed using SmartPLS and SPSS. The findings reveal that AI's perceived benefits and ease of use significantly influence its adoption in SMEs, along with organizational support, readiness, and the technological environment. Perceptions of technology, organizational compatibility, and readiness play a critical role in the adoption process. The study provides valuable insights for managers and businesses, highlighting the driving and hindering factors of AI adoption. It suggests that understanding these factors can help SMEs develop strategies to optimize AI adoption, enhance business performance, and support digital transformation. Additionally, the research emphasizes the importance of a supportive technological and organizational environment, contributes to understanding AI adoption in SMEs in Vietnam, and offers practical recommendations for managers and government agencies to foster favorable conditions for embracing new technologies like AI.

**Keywords:** Artificial Intelligence (AI); SMEs; Technology Adoption; TAM-TOE Model; Leadership Support; Digital Transformation; Industry 4.0

## 1. Introduction

The rapid development of technology, particularly Artificial Intelligence (AI), has transformed industries worldwide. However, the adoption of AI remains challenging, especially for small and medium-sized Enterprises (SMEs) in emerging markets like Vietnam. Vietnamese SMEs, which make up over 98% of businesses and employ 70% of the workforce (Trinh & Thanh, 2017), face significant barriers to adopting AI, such as limited financial resources, lack of technical expertise, and insufficient infrastructure. This study explores AI adoption in Vietnamese SMEs using an integrated model combining the Technology Acceptance Model (TAM) and the Theory of Organizational Environment (TOE).

TAM focuses on two key factors: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), which drive individual technology adoption. However, for SMEs, organizational and environmental factors also play a crucial role. TOE expands on this by considering technological, organizational, and environmental contexts, such as management support, IT infrastructure, market competition, and regulatory policies (Omowole, Olufemi-Philips, et al., 2024).

Despite growing awareness of AI's potential, adoption rates among Vietnamese SMEs are low, hindered by high costs, complexity, and a shortage of skilled labor. This research aims to identify the key determinants of AI adoption, including internal readiness and external pressures, and provide practical recommendations for overcoming barriers. By integrating TAM and TOE, the study offers valuable insights for both SMEs and policymakers to support the successful integration of AI in Vietnam’s SME sector.

## 2. Theoretical background

### *2.1. AI and AI adoption*

Artificial Intelligence (AI) has emerged as one of the most transformative digital technologies of the 21st century, enabling machines to perform tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and language processing (Russell & Norvig, 2016). While AI is often grouped under the broader umbrella of digital technologies, it is fundamentally different in terms of complexity, decision-making autonomy, and data dependency. Unlike conventional information systems—such as ERP, cloud computing, or business intelligence tools—AI systems can adapt and evolve through continuous learning, allowing organizations to automate unstructured decision-making processes and uncover hidden patterns within large datasets (Dwivedi et al., 2021).

The adoption of AI by small and medium-sized enterprises (SMEs) presents a distinct set of challenges that go beyond those associated with traditional digital technologies. These include a lack of specialized technical expertise, insufficient data infrastructure, high implementation costs, and organizational resistance due to perceived risks and ethical concerns (Wamba-Taguimdje et al., 2020; Ransbotham et al., 2018). For SMEs in developing economies like Vietnam, these barriers are further compounded by limited access to external funding, weak regulatory frameworks, and the absence of national AI strategy awareness (Le et al., 2024). Moreover, the intangible nature of AI’s return on investment often makes it difficult for SME leaders to justify early adoption, despite its potential to significantly enhance productivity, decision-making, and customer engagement (Janssen et al., 2020).

On the other hand, AI also presents unique adoption drivers. These include increased pressure to stay competitive, the availability of scalable AI-as-a-Service platforms, and the rising demand for real-time data-driven decision-making. Organizational agility, leadership support, and data-readiness have also been identified as critical internal enablers, while external drivers include technological infrastructure, market dynamics, and government support programs (Kar et al., 2021;

and Cubric, 2020). These AI-specific factors warrant a focused theoretical framework to better understand their interplay and impact on adoption behavior.

### *2.2. Organizational competency (OCM)*

Organizational competency refers to the skills, knowledge, abilities, and other relevant characteristics that employees need to perform effectively in their roles (Long et al., 2013). The TOE framework highlights the importance of organizational competency (Alarjani, 2019). Competency is a multifaceted concept, with employee competency directly contributing to the overall competency of the organization (Vargas-Halabí et al., 2017). It is closely linked to performance (Tortorella et al., 2019), and therefore, to maintain a performance-driven culture, an organization needs competent employees. When employees are proficient in using a system, it reflects the organization's overall competency. On the other hand, if employees lack the capability to use technology, they are unlikely to recognize its usefulness (Maduka et al., 2018).

*H1: Organizational competency positively impacts perceived usefulness.*

### *2.3. Organizational complexity (OCX)*

The concept of complexity in an organization comes from the sense of ease of use lent from TAM, as already discussed. Complexity refers to the challenges and obstacles involved in understanding and using a system (Chatterjee, Rana, et al. 2021). When considering AI adoption in an organization, this complexity is seen as an internal issue, assessed by factors such as the extent of AI infrastructure usage, the time required to complete tasks, the effectiveness of intelligent decision-making, system functionality, and the design of the interface (Parveen & Sulaiman, 2008). As organizational complexity increases, both perceived usefulness and ease of use tend to decline. If a system is complex, employees may struggle to use new technology effectively and fail to recognize its benefits (Chatterjee, Rana, et al., 2021).

*H2a: Organizational complexity negatively impacts perceived usefulness.*

*H2b: Organizational complexity negatively impacts perceived ease of use.*

### *2.4. Organizational readiness (ORE)*

Organizational readiness is described as the availability of necessary organizational resources for adopting new technologies (Iacovou et al., 1995). The ability of an organization to adopt innovative technologies is influenced by factors such as its size and resource availability, which are crucial for assessing its readiness. The size of an organization directly impacts its preparedness for adopting new technologies (Ghaleb et al., 2021). Larger organizations typically require more technical and financial resources to support technology adoption (Aboelmaged, 2014). When an organization lacks the readiness to implement new technologies like AI, employees may feel limited in using the system, thus failing to recognize its usefulness.

*H3a: Organizational readiness positively impacts perceived usefulness.*

*H3b: Organizational readiness positively impacts perceived ease of use.*

### *2.5. Organizational compatibility (OCO)*

Organizational compatibility (OCO) refers to how well an innovation aligns with potential users' values, experiences, and requirements (Chatterjee, Rana et al., 2021). For organizations, compatibility is an internal issue, focusing on how an organization’s existing behavior, values, and experience align with new technologies (Kishore & McLean, 2007). In practical terms, organizational compatibility concerns how easily innovations like AI can be integrated into existing processes and infrastructure.

*H4a: Organizational compatibility positively impacts perceived usefulness.*

*H4b: Organizational compatibility positively impacts perceived ease of use.*

### *2.6. Competitive advantage (COA)*

Competitive advantage is defined as the extent to which a technological innovation offers more benefits compared to alternatives. The advantages provided by a technology in comparison to alternatives are a key driver in its adoption within an organization. Competitive pressure to maintain or enhance advantages is a significant factor in the diffusion of innovation (Yang et al., 2015). AI adoption is often seen as a way for organizations to gain a competitive edge, promoting innovation and creating new opportunities (Fast & Horvitz, 2017). Achieving a competitive advantage can influence employees' perceptions, as they may become complacent when their organization is at the forefront (Pietersen, 2010). Competitive advantage also has a socio-environmental aspect developed through the use of AI-based technologies (Makridakis, 2017). AI technologies such as machine learning, deep learning, and natural language processing help organizations gain competitive advantages (Rane et al., 2024). When employees are adequately trained, they are more likely to perceive the technology as useful and easy to use.

*H5a: Competitive advantage positively impacts perceived usefulness.*

*H5b: Competitive advantage positively impacts perceived ease of use.*

*H5c: Competitive advantage positively impacts the intention to adopt AI.*

### *2.7. Partner support (PSU)*

Partner support (PSU) is crucial in maximizing the potential of any innovation. Beyond financial assistance, partner support acts as an external force that helps organizations develop the knowledge base of their employees, which is essential for adopting advanced technologies like AI (Zheng et al., 2015). This support is key to enhancing organizational innovation by facilitating knowledge exchange (Koka & Prescott, 2002). The development of employees’ knowledge, both independently and through partner collaboration, makes AI adoption easier. This knowledge helps employees see the value of AI in their organizations (Asgari et al., 2017) and increases the perceived ease of use as they become more proficient in using the technology. Partner support plays a significant role in fostering this knowledge, thus contributing to the successful adoption and use of AI in HRM (Hottenrott & Lopes-Bento, 2016).

*H6a: Partner support positively impacts perceived usefulness.*

*H6b: Partner support positively impacts perceived ease of use.*

*H6c: Partner support positively impacts the intention to adopt AI.*

### *2.8. Perceived usefulness (PU) and Perceived ease of use (PEOU)*

Perceived usefulness (PU) is defined as the extent to which users believe that using a system or technology will enhance their job performance (Lee et al., 2003). TAM has been widely used to describe how individuals accept new systems or technologies, and this study helps explain AI adoption in firms. Additionally, perceived ease of use (PEOU) refers to the belief that using a new system would require little effort (Davis, 1989). Several studies have used TAM to describe technology acceptance (Lee et al., 2003), and it shows that PEOU is a predictor of perceived usefulness.

*H7: Perceived ease of use positively impacts perceived usefulness.*

According to TAM, PEOU also acts as a predictor of users' intention to adopt new technologies, as users are more likely to adopt technologies they find easy to use (Yousafzai et al., 2007). TAM has been recognized as a key model for explaining the intention to use new technologies (Venkatesh & Morris, 2003). Studies on the adoption of various technologies, such as e-commerce and multipurpose devices, show that ease of use is a key predictor of adoption intention.

*H8: Perceived ease of use positively impacts the intention to adopt AI.*

Perceived usefulness is interpreted as the potential users' subjective possibility that using a system or the application of a system will enhance the job performance of the users within the context of the firm (Lee et al., 2003). Ajzen (1991) believed that the perceived usefulness of a technology will motivate users to intend to use that technology. In this study, TAM has been used to explain use intention by users since this model has demonstrated that there exists a linear relationship between usefulness and intention. PU includes the concepts of subjective norms, image, job relevance, output quality, and result demonstrability (Venkatesh & Bala, 2008). These predictors prompted us to construe that individuals form perceived usefulness judgments partly due to cognitively comparing what a system is capable of doing with what they need to accomplish in their job (Venkatesh & Davis, 2000). Hence, it is perceived that a sense of usefulness would lead an individual to intend to use a new technology.

*H9: Perceived usefulness positively impacts the intention to adopt AI.*

### *2.9. Effects of leadership support (LS) as a moderator*

Leadership support (LS) is associated with the sincere engagement of a higher-ranking leader in the implementation of the new system, which would affect the relation between perceived usefulness and intention, as well as the perceived ease of use and intention (Ifinedo, 2011). Leadership commitment is considered to have a significant impact on the adoption of innovative technology (Yang et al., 2015). As an example, in the context of the research on information science, leadership support was considered important for promoting cloud computing adoption, as well as the adoption of electronic business (Yang et al., 2015). In this study, we considered LS as a variable moderating the two linkages covering H8 (PEOU to IAA) and H9 (PU to IAA).

*H10a: Leadership support moderates the linkage between perceived usefulness and the intention to adopt AI.*

*H10b: Leadership support moderates the linkage between perceived ease of use and the intention to adopt AI.*

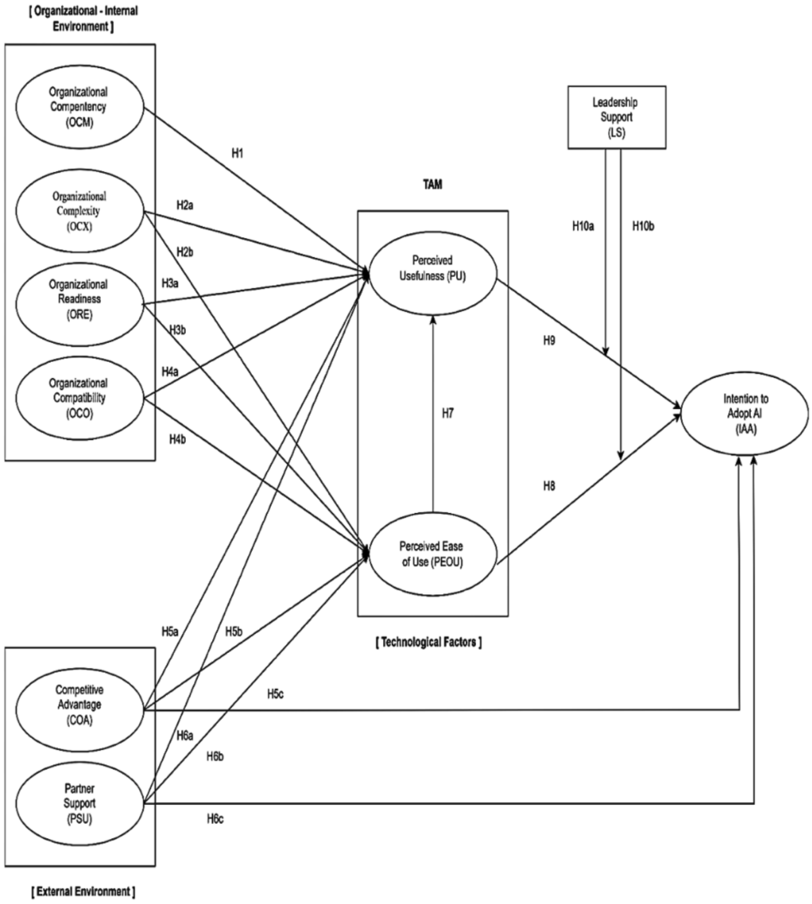


***Fig. 1. Conceptual model.***

## 3. Methodology

This research examines the factors influencing the adoption of artificial intelligence (AI) technology in Vietnamese SMEs, using an integrated TAM-TOE model. Data collection will involve online surveys distributed through Google Forms, and QR codes will facilitate access for employees, managers, and CEOs of SMEs in Vietnam for one and a half months from November 24, 2024, to January 18, 2025. The data collection targeted SMEs nationwide from diverse industries and company sizes, ensuring a comprehensive dataset. Before analysis, responses were screened for completeness and accuracy, and any incomplete or inconsistent entries were removed. The processed data was then structured for statistical analysis using SmartPLS and SPSS. Furthermore, the snowball sampling technique will be employed to extend the reach of the survey. In this approach, the survey link will initially be sent to a core group of friends, colleagues, and known contacts via social media. These initial respondents will then be encouraged to forward the survey link to their own networks, such as friends, family members, and professional associates, thereby creating a "snowball" effect.

Organizational-Internal Environment is divided into four variables. The organizational competency construct was measured using the four-item Organizational Competency Scale, which was developed by Long et al. (2013) and Maduka et al. (2018), while the measurement of Organizational Complexity was carried out by using the OCX scale adapted by Sonnenwald et al. (2001), Idris (2015), Parveen & Sulaiman (2008), including four items.

External factors encompass competitive advantage and partner support. To assess competitive advantage, four items from Rogers (2003), Yang (2015), and Makridakis (2017) were utilized. These items aimed to capture different aspects of competitive advantage. For example, participants were asked to rate their level of agreement with statements such as "I am aware that some competitors have adopted AI technology in their operations."

In terms of technological factors, to evaluate perceived usefulness, four items adapted by Davis(1989) and Lee et al. (2003) were employed.

The measurement of Intention to Adopt AI was conducted using a four-item scale developed by Yousafzai et al. (2007), including "I fully support the use of AI in our business processes."

For the assessment of leadership support, items from the scale provided by de Vries, Bekkers, and Tummers (2016) were adopted. These items sought to capture diverse facets of LS. For instance, respondents were requested to assess their level of concurrence with some statements, such as "My leader effectively leads and manages change.", and “My leader encourages innovation and creativity.”

## 4. Results

### *4.1. Demographic characteristics*

The demographic analysis reveals that among the 309 participants, the majority were female, accounting for 68% of the total sample. The age group of 20–30 years was predominant, with 232 individuals, while only a small proportion (15%) of respondents were over the age of 40.

In terms of educational attainment, 268 out of 309 participants held a university degree, whereas only 4.5% had completed education at the high school level. Most respondents reported having less than five years of work experience, representing 67.6% of the sample. Notably, only two individuals had more than 15 years of service in their respective organizations.

Regarding company size, the majority were employed in organizations with 10 to 50 employees, comprising 29.4% of respondents. In terms of occupational position, the vast majority identified as employees (81.2%), in contrast to a smaller proportion who held managerial (16.2%) or CEO (2.6%) roles.

### *4.2. Measurement model*

#### *4.2.1. Reliability and validity assessment*

Reliability is a key aspect of assessing the quality of measurement scales. Composite Reliability (CR) is often preferred over Cronbach's Alpha as it provides a more accurate assessment of scale reliability. Cronbach's Alpha can underestimate the true reliability compared to CR. According to Chin (1998), a CR value of 0.6 or higher is required for exploratory research, while a threshold of 0.7 is appropriate for confirmatory studies (Henseler, 2013). Other researchers, including Hair et al. (2021) and Bagozzi & Yi (1988), also recommend a CR threshold of 0.7 for most research contexts. Additionally, Cronbach's Alpha values should be ≥ 0.7 (DeVellis, 2021), and the Average Variance Extracted (AVE) should exceed 0.5 (Fornell & Larcker, 1981).

Based on the analysis, most constructs exhibit strong reliability and validity, with Cronbach’s Alpha and Composite Reliability (CR) values exceeding 0.7, and AVE values above 0.5. Although the OCX construct has a lower Cronbach’s Alpha (0.541), its CR (0.806) and AVE (0.677) meet the recommended thresholds, indicating that the construct still retains acceptable reliability and validity.

*4.2.2. Discriminant validity*

Discriminant validity checks whether each variable in the model is truly different from the others (Hair & Alamer, 2022). This ensures that each variable measures a unique aspect and does not overlap with other variables. To test this, the study uses the Fornell and Larcker criterion (Fornell & Larcker, 1981). According to this method, the square root of the Average Variance Extracted (AVE) for each variable should be higher than its correlation with any other variable in the model (Hair et al., 2012). From the available data, the constructs COA, IAA, LS, OCM, OCO, OCX, ORE, PEOU, PSU, and PU demonstrate good discriminant validity, as the square roots of their AVE values are higher than their correlations with other constructs. This confirms that each latent variable is statistically distinct and does not overlap with other constructs in the model.

*4.2.3. Exploratory factor analysis (EFA)*

According to the findings, the Kaiser-Meyer-Olkin (KMO) coefficient of 0.926 indicates excellent sampling adequacy for factor analysis. Also, Bartlett's test of sphericity is significant ($p = 0.000 < 0.05$), confirming that the variables are sufficiently correlated. According to the Eigenvalue criterion, factors with values greater than 1 should be retained; in this analysis, eight such factors were identified. These factors collectively explain 66.285% of the total variance, exceeding the 50% threshold recommended by Hair et al. (2012), thereby confirming the appropriateness and reliability of the exploratory factor analysis (EFA) model used in this study.

In PLS-SEM, outer loadings indicate the strength of the relationship between an observed variable and its corresponding latent construct. A loading of at least 0.708 is recommended to ensure that the latent variable explains at least 50% of the variance in the observed variable (Hair et al., 2021). Based on the Pattern Matrix results, some items—specifically OCM3 (0.611), OCX3 (0.541), and OCX4 (0.585)—did not meet the 0.7 threshold. Following Hair et al. (2010), OCX3 and OCX4 were removed to enhance the model's reliability and validity. The factor analysis was then rerun, and all remaining items showed loadings above 0.7, confirming a stronger association between observed variables and their respective constructs. This adjustment improved the overall model fit and confirmed the appropriateness of the revised measurement model.

### *4.3. Confirmatory factor analysis (CFA)*

Table 1 shows that the model fit indices indicate a reasonable level of fit with the research data. Although the NFI index is below the desired threshold of 0.90, with values of 0.692 for the saturated model and 0.688 for the estimated model, other indices like d_ULS, d_G, and SRMR fall within the acceptable range, suggesting a good overall fit. Given these results, the model does not require significant adjustments and can be used for further analysis in the study.

***Table 1. Model fit criteria result.***

| Index | Result | Evaluation |
|---|---|---|
| d_ULS | 3.447 | Good |
| d_G | 1.324 | Good |

| | | |
|---|---|---|
| SRMR | 0.070 | Good |
| NFI | 0.692 | Good |
| Chi-square | 2282.847 | Good |

Hair, Risher et al. (2019) suggest that if the collinearity statistics (VIF) is 5 or higher, the model is highly likely to experience multicollinearity. If the VIF falls between 3 and 5, multicollinearity may occur, and if the VIF is below 3, multicollinearity is less likely to be present. Based on the analysis, the VIF confirms that there are no significant multicollinearity issues in the regression model. All VIF values are below the threshold of 5, with most values being under 2.5, ensuring the independence of the variables. The interactions between LS x PU and LS x PEOU show no signs of multicollinearity. Therefore, the regression model in this study is reliable and does not require further adjustments.

***4.4. Structural equation modeling (SEM)***

SEM is a key method for analyzing complex relationships among variables, allowing researchers to assess both direct and indirect effects and the model's predictive power (Haenlein & Kaplan, 2004). Essential steps in SEM include checking collinearity, evaluating path relationships, and interpreting coefficients and the Coefficient of Determination ($R^2$) (Hair & Alamer, 2022). After confirming no collinearity issues, hypotheses are tested using p-values; a value below 0.05 indicates statistical significance (Hair et al., 2021). Path coefficients show the strength and direction of effects, with higher absolute values indicating stronger relationships. In Table 2, the Original Sample (O) and p-value (P) columns were examined. Based on Chatterjee, Rana et al. (2021), and Hair & Alamer (2022), most relationships were statistically significant, with the highest p-value among supported hypotheses at 0.008. Significant paths include H3a, H3b, H4a, H4b, H5a, H5c, H6a, H6b, H8, H9, H10a, and H10b. However, hypotheses H1, H2a, H2b, H5b, H6c, and H7 were not supported, as their p-values exceeded 0.05.

***Table 2. Structural model results.***

| | **Original Sample (O)** | **p-value** |
|---|---|---|
| COA → IAA | 0.386 | 0.000 |
| COA → PEOU | 0.064 | 0.266 (rejected) |
| COA → PU | 0.553 | 0.000 |
| OCM → PU | -0.035 | 0.563 (rejected) |
| OCO → PEOU | 0.318 | 0.001 |
| OCO → PU | 0.186 | 0.004 |
| OCX → PEOU | 0.038 | 0.466 (rejected) |
| OCX → PU | 0.025 | 0.606 (rejected) |
| ORE → PEOU | 0.271 | 0.001 |
| ORE → PU | -0.147 | 0.027 |
| PEOU → IAA | 0.111 | 0.032 |

| | | |
|---|---|---|
| PEOU → PU | 0.119 | 0.104 (rejected) |
| PSU → IAA | 0.017 | 0.755 (rejected) |
| PSU → PEOU | 0.214 | 0.002 |
| PSU → PU | 0.219 | 0.000 |
| PU → IAA | 0.225 | 0.008 |
| LS x PU → IAA | -0.282 | 0.000 |
| LS x PEOU → IAA | 0.292 | 0.000 |

Analysis of indirect effects reveals that competitive advantage (COA) has the strongest influence on AI adoption through perceived usefulness (PU), with COA → PU → IAA = 0.125, followed by PSU → PU → IAA = 0.049, and → PU → IAA = 0.042 suggesting that partner support and organizational compatibility contribute to AI adoption through PU. Additionally, OCO → PEOU → IAA = 0.035 and organizational readiness (ORE) → PEOU → IAA = 0.030, highlighting the role of perceived ease of use (PEOU). However, OCM → PU → IAA = -0.008 and ORE → PU → IAA = -0.033, indicating organizational complexity and organizational readiness do not always facilitate AI adoption through PU.

***Table 3. Hypothesis testing summary.***

| **Hypothesis** | | **p-value** | **Evaluation** |
|---|---|---|---|
| H1 | OCM → PU | 0.563 | Rejected |
| H2a | OCX → PU | 0.606 | Rejected |
| H2b | OCX → PEOU | 0.466 | Rejected |
| H3a | ORE → PU | 0.027 | Accepted |
| H3b | ORE → PEOU | 0.001 | Accepted |
| H4a | OCO → PU | 0.004 | Accepted |
| H4b | OCO → PEOU | 0.001 | Accepted |
| H5a | COA → PU | *** | Accepted |
| H5b | COA → PEOU | 0.266 | Rejected |
| H5c | COA → IAA | *** | Accepted |
| H6a | PSU → PU | *** | Accepted |
| H6b | PSU → PEOU | 0.002 | Accepted |
| H6c | PSU → IAA | 0.755 | Rejected |
| H7 | PEOU → PU | 0.104 | Rejected |
| H8 | PEOU → IAA | 0.032 | Accepted |
| H9 | PU → IAA | 0.008 | Accepted |
| H10a | LS x PU → IAA | *** | Accepted |
| H10b | LS x PEOU → IAA | *** | Accepted |

**5. Discussion**

This study offers valuable insights into the factors influencing AI adoption in Vietnamese SMEs. By applying the integrated TAM-TOE framework, the research confirms several significant relationships that contribute to the theoretical and practical understanding of AI adoption in SMEs.

The findings indicate that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are pivotal factors influencing the Intention to Adopt AI (IAA). These results align with established technology adoption models (Davis, 1989), where both ease of use and perceived benefits are critical drivers of adoption decisions. In the context of Vietnamese SMEs, the perceived benefits and ease of use of AI significantly increase the likelihood of adoption. Organizations should thus ensure that AI technologies are both effective and user-friendly to maximize adoption potential.

Further, organizational and technological factors such as Organizational Readiness (ORE), Organizational Compatibility (OCO), Competitive Advantage (COA), and Partner Support (PSU) demonstrated significant positive effects on both PU and PEOU. This highlights that a favorable internal environment, characterized by technology readiness, system compatibility, and external partnerships, is key in shaping perceptions of AI. Leadership Support (LS) is a crucial moderating factor, strengthening the relationships between PU and IAA, as well as PEOU and IAA. This finding emphasizes the importance of leadership in fostering an environment conducive to AI adoption. Strong leadership is vital for allocating necessary resources, addressing challenges, and promoting AI initiatives, thus demonstrating that AI adoption requires a strategic, top-down commitment.

This study enriches the literature on the adoption of AI, particularly in the context of SMEs in Vietnam. It underscores that PU and PEOU are primary drivers of IAA and highlights the significance of organizational factors such as readiness, compatibility, competitive advantage, and leadership support. The research emphasizes that AI adoption is not merely a technological challenge, but also a strategic decision that involves shifting organizational culture and leadership strategies.

Several hypotheses were supported by the empirical results. For example, both Organizational Readiness (H3a and H3b) and Organizational Compatibility (H4a and H4b) were found to have significant positive effects on PU and PEOU, respectively. These findings are consistent with previous research indicating that when organizations are well prepared and when their existing systems align with new technologies, users tend to perceive the technology as both useful and easy to use (Zhu et al., 2003; Wang et al., 2010). Moreover, Competitive Advantage (H5a and H5c) positively influenced PU and IAA, supporting the notion that firms perceiving a strategic edge are more inclined to adopt AI (Khan et al., 2024). Similarly, Partner Support (H6a and H6b) was shown to positively affect both PU and PEOU, and Leadership Support (H10a and H10b) significantly moderated the relationships between PU and IAA, as well as between PEOU and IAA. These results underscore the importance of strong internal leadership and supportive external relationships in driving the adoption process (Anwar, Zong et al. 2024).

However, certain hypotheses were rejected based on the study's findings

***H1: Organizational Competency → Perceived Usefulness (PU) (Rejected)***

The research results indicate that organizational competency does not significantly affect the perceived usefulness of AI. In simple terms, even if a company possesses strong internal capabilities—such as a skilled workforce and robust technological infrastructure—this does not automatically lead to a higher perception of the benefits that AI can bring.

One main reason for this is that Vietnamese SMEs often face significant pressure to address short-term operational challenges, such as maintaining profitability and reducing costs, rather than focusing on long-term strategic investments like AI adoption. Many of these SMEs lack operational stability and do not have dedicated technology departments needed to fully leverage advanced technologies. As a result, even if these organizations are technically competent, their employees may not immediately recognize the long-term benefits of AI; instead, AI is viewed as an investment with delayed returns (Ifinedo, 2011).

***H2a: Organizational Complexity → Perceived Usefulness (PU) (Rejected)***

The hypothesis that organizational complexity reduces the perceived usefulness of AI was not supported because our data indicate that SMEs in Vietnam generally have simple structures and work processes. This means that in the context of these SMEs, potential difficulties arising from complex organizational structures—such as overlapping roles, slow decision-making, and complicated internal communication—do not occur to a significant extent. Vietnamese SMEs tend to focus on optimizing daily operations and achieving quick business efficiency, so they primarily assess the usefulness of AI based on its ability to increase productivity, reduce costs, and improve workflow. In other words, although complexity might theoretically pose a barrier, in SMEs with small scale and simple structures, its negative impact on the perceived usefulness of AI is minimal (Chatterjee et al., 2021).

***H2b: Organizational Complexity → Perceived Ease of Use (PEOU) (Rejected)***

Similarly, the hypothesis that organizational complexity negatively affects the perceived ease of use of AI was not supported. In Vietnamese SMEs, the simplicity of organizational structure and work processes facilitates the integration and use of AI. SMEs typically have fewer management layers and less cumbersome internal processes, so organizational barriers do not hinder the evaluation of how easy it is to use new technology.

Accordingly, the perceived ease of use of AI is mainly determined by intrinsic factors of the technology—such as the design of the user interface, system quality, and the effectiveness of training programs—rather than by the organization’s structure (Venkatesh et al., 2003; Chatterjee & Kar, 2018). Because SMEs are inherently simple and flexible, even if there is some degree of complexity, it does not significantly affect how employees evaluate the ease of using AI.

***H5b: Competitive Advantage → Perceived Ease of Use (PEOU) (Rejected)***

Although competitive advantage significantly affects perceived usefulness and the overall intention to adopt AI, our study did not support that it positively impacts perceived ease of use. This suggests that while competitive advantage may help highlight the strategic and economic benefits of AI, it does not necessarily make the technology easier to use. According to (Davis 1989) and (Venkatesh, Morris, et al., 2003), ease of use is primarily determined by intrinsic factors of the technology, such as system design, user interface quality, and the effectiveness of training programs. In contrast, competitive advantage is an external strategic variable that reflects a company's market position rather than its operational or technical characteristics. Therefore, even a highly competitive company may still have technology that is difficult to use if those intrinsic factors are not addressed.

***H6c: Partner Support → Intention to Adopt AI (IAA) (Rejected)***

The research shows that while Partner Support (PSU) improves the perceived usefulness (PU) and ease of use (PEOU) of AI, it does not directly influence the intention to adopt AI (IAA) in organizations (Nguyen & Simkin, 2017; Khan et al., 2024). External support may enhance perceptions of AI, but without internal alignment and leadership commitment, it does not motivate businesses to adopt the technology (Dey, Chowdhury, et al., 2024).

For Vietnamese SMEs, internal factors like strong leadership and organizational readiness are crucial in the AI adoption decision-making process (Ifinedo, 2011). Even with external support, if a company's leadership is not aligned or committed to investing in AI, adoption is unlikely (Venkatesh et al., 2003). External support can help businesses recognize AI's benefits, such as improved efficiency and competitive advantage, but without internal decisiveness, these benefits won't lead to actual adoption (Khan et al., 2024).

In conclusion, while partner support is valuable for understanding AI's potential, it does not directly drive AI adoption without strong internal commitment and a unified vision within the organization (Nguyen & Simkin, 2017).

***H7: Perceived Ease of Use → Perceived Usefulness (Rejected)***

Contrary to the traditional Technology Acceptance Model (TAM), this study found no significant relationship between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) within the context of Vietnamese small and medium-sized enterprises (SMEs). Rather than being influenced by usability, SMEs tend to evaluate AI technologies based on their direct economic and strategic benefits, such as productivity gains and cost savings. This aligns with Hess, McNab, et al. (2014), who argue that the ease-of-use–usefulness relationship is context-dependent. In highly competitive and resource-constrained environments like Vietnam, factors such as "perceived economic benefit" and "strategic fit" likely play a more critical role in shaping usefulness perceptions. The lack of these variables in the current model may explain why PEOU did not significantly influence PU. Future studies should incorporate such context-specific variables to improve the model's explanatory power. These findings suggest that Vietnamese SMEs prioritize measurable outcomes over usability when assessing new technologies, prompting a need to adapt TAM to better suit local business realities.

## 6. Limitations and recommendations for future research

The study on AI adoption in Vietnamese SMEs has several limitations that should be considered when interpreting its findings. The sample size of 309 responses, primarily from Da Nang, Ho Chi Minh City, and Hanoi, may not fully represent the diversity of SMEs across Vietnam. As AI adoption varies by region, the study's findings may not accurately reflect the experiences of SMEs in other provinces, limiting the generalizability of the results.

Methodologically, the referral-based sampling method could have resulted in inaccuracies in identifying companies that meet SME criteria, affecting the sample's representativeness. Additionally, the cross-sectional design only captured data at a single point in time, preventing an analysis of trends or changes in factors such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and the Intention to Adopt AI (IAA) over time.

Scope limitations include the use of the TAM-TOE model, which focuses on technological, organizational, and environmental factors but overlooks social, cultural, and emotional influences on AI adoption. The study also did not address critical concerns like data security and privacy, which could hinder AI adoption. Lastly, the research did not consider financial constraints and other non-technical factors that impact successful AI implementation, further limiting the study's scope and practical applicability.

Due to these mentioned limitations, this study offers valuable insights into AI adoption in Vietnamese SMEs but highlights several areas for future research. Firstly, the cross-sectional design limits the ability to assess changes over time. Future studies should adopt a longitudinal approach, tracking perceptions of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Intention to Adopt AI (IAA) at multiple points to provide a dynamic understanding of adoption trends.

In terms of the study's sample, concentrated in Da Nang, Hanoi, and Ho Chi Minh City, may not fully reflect the diversity of SMEs across Vietnam. Expanding the geographic scope in future research will enhance generalizability and offer a broader view of AI adoption factors.

Social and cultural factors, such as leadership support and employee motivation, were not addressed but are crucial for AI adoption. Future research should explore how these elements interact with organizational and technological factors.

Additionally, integrating internal (e.g., leadership, culture) and external factors (e.g., competition, infrastructure) would offer a deeper understanding of AI adoption. The use of fuzzy-set Qualitative Comparative Analysis (fsQCA) could help identify complex causal relationships.

Finally, data security and privacy concerns, significant barriers to AI adoption, should be explored in future studies, along with the moderating role of leadership support in fostering a conducive environment for AI implementation.

## ACKNOWLEDGEMENT

We would like to express our sincere gratitude to the COMBELT 2025 organisers for offering us a chance to contribute to this academic conference, and anonymous reviewers for their insightful comments and valuable feedback, which helped improve the quality of the paper. We also extend our appreciation to VNUK Institute for providing the academic environment and support necessary for this research.

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## APPENDICES

**Appendix A: Questionnaire design**

| | Variables | Items | References |
|---|---|---|---|
| **Organizational-Internal Environment** | Organizational Competency (OCM) | OCM1: We have sufficient technology to maintain and address any issues that may arise when integrating AI into our current business processes. | Adapted by Long et al. (2013), Maduka et al. (2018) |
| | | OCM2: Having specialized technological resources at the organizational level is crucial for effectively adopting AI. | |
| | | OCM3: We have AI experts within our organization. | |
| | | OCM4: Organizations with AI-trained personnel will gain a competitive advantage in the market. | |
| | Organizational Complexity (OCX) | OCX1: Adopting AI technology is more flexible compared to our existing systems. | Adapted by Sonnenwald et al. (2001), Idris (2015), |

| | | | |
|---|---|---|---|
| | | OCX2: Adopting AI technology in our processes may pose risks as many procedures would need automation. | Parveen & Sulaiman (2008) |
| | | OCX3: Integrating AI into our current system is a complex task for our company. | |
| | | OCX4: Employees often resist transitioning from legacy systems to AI-based systems. | |
| | Organizational Readiness (ORE) | ORE1: I find it easy to understand the process of adopting AI in our company. | Adapted by Iacovou et al. (1995), Aboelmaged (2014), and Idris (2015) |
| | | ORE2: I have the necessary resources to learn and use AI technology in my company.<br>ORE3: We have multiple methods (online, in-person, etc.) for training staff on AI within the organization. | |
| | | ORE4: I feel that learning and applying AI technology is easy. | |
| | Organizational Compatibility (OCO) | OCO1: We have a well-planned approach to integrate AI with our existing systems. | Adapted by Peng et al. (2012) and Geczy et al. (2012) |
| | | OCO2: Our partners support the integration of AI technology into our current processes. | |
| | | OCO3: AI technology is compatible and easily integrates with our current business processes. | |
| | | OCO4: It is easy to customize the AI-based system to meet our needs. | |
| **External Environment** | Competitive Advantage (COA) | COA1: I am aware that some competitors have adopted AI technology in their operations. | Adapted by Rogers (2003), Yang (2015), |

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|---|---|---|---|
| | | COA2: I believe that using AI will bring a competitive advantage to my business. | and Makridakis (2017) |
| | | COA3: AI is essential for us to maintain our competitive position. | |
| | | COA4: I am aware that many companies are transitioning to AI-based systems. | |
| | Partner Support (PSA) | PSA1: Partner support is necessary when we transition from legacy systems to AI. | Adapted by Zheng & Yang (2015), and Haans et al. |
| | | PSA2: Partner support makes the AI adoption process easier. | |
| | | PSA3: Our partners help quickly resolve technical issues as they arise. | |
| | | PSA4: Partner support helps reduce costs for our business when adopting AI. | |
| **Technological Factors** | Perceived Usefulness (PU) | PU1: I agree that using AI helps our business operate more efficiently. | Adapted by Davis (1989) and Lee et al. (2003) |
| | | PU2: Using AI increases productivity within the organization. | |
| | | PU3: I complete tasks faster when using AI-based systems. | |
| | | PU4: AI-based systems help reduce operating costs. | |
| | Perceived Ease Of Use (PEOU) | PEOU1: The process of using the AI system is easy to understand. | Adapted by Lee et al. (2003), and Yousafzai et al. (2007) |
| | | PEOU2: Our business finds it easy to operate the AI-based system. | |
| | | PEOU3: I am confident that I can easily use the AI system in my work. | |
| | | PEOU4: I believe all relevant employees can quickly learn to use AI technology. | |

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|---|---|---|
| Intention to Adopt AI (IAA) | IAA1: I think that the AI system brings benefits to my company. | Adapted by Yousafzai et al. (2007) |
| | IAA2: I fully support the use of AI in our business processes. | |
| | IAA3: I want to take full advantage of AI technology in my work. | |
| | IAA4: Overall, I believe AI will enhance productivity for our company. | |
| Leadership Support (LS) | LS1: My leader engages with staff on how to respond to future challenges. | Adapted by deVries, Bekkers & Tummers (2016) |
| | LS2: My leader gives their time to identify and develop talented people. | |
| | LS3: My leader effectively leads and manages change. | |
| | LS4: My leader encourages innovation and creativity. | |